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Welfare Dependence, Recidivism, and the Future for Recipients of Temporary Assistance for Needy Families (TANF)

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Keywords

child support, recidivism, semiparametric, single-parent, welfare dependence

Disciplines

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Abstract

This paper examines welfare participation dynamics during 1993–96, the initial years of Iowa's welfare reform, a reform remarkably similar to the state's current Temporary Assistance for Needy Families (TANF) program. Analyses of the Family Investment Program (FIP) participation over the program's first two years show that, on average, FIP recipients stayed fewer months in the second year compared with the first, although a relatively large share of participants (36 percent) stayed on for the full two years. A fixed effects model and a semiparametric duration model are used to examine welfare dependence and recidivism. Iowa's experience suggests that human capital, child support, marital status, and the presence of children will be significant factors in reducing time on TANF and recidivism. Child support and wage income are crucial in determining the degrees of success for exiting and staying off, especially during the early months of the exit.

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WELFARE DEPENDENCE, RECIDIVISM, AND THE FUTURE FOR RECIPIENTS OF TEMPORARY ASSISTANCE FOR NEEDY FAMILIES (TANF)

Introduction

Welfare programs were originally designed to alleviate poverty among single-parent families during economic downturns. Although these public assistance programs did provide a safety net for people in need, often they were linked to undesirable outcomes, such as increased out-of-wedlock births, and were thought to create disincentives for recipients to work. The Temporary Assistance for Needy Families (TANF) program was established under the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) in 1996 with the explicit objectives of: (1) providing assistance to needy families; (2) ending welfare dependence by promoting job preparation, work, and marriage; (3) preventing and reducing out-of-wedlock pregnancies; and (4) encouraging the formation and maintenance of two-parent families. TANF tightens benefit eligibility criteria by implementing a five-year lifetime limit on receiving benefits, invoking stricter work and education requirements to qualify for benefits, and strengthening the enforcement of child support obligations. Although state governments now have nearly full authority to administer their TANF programs, they will be required to have 50 percent of the program participants involved in approved work activities by 2002, or face sanctions in the form of reduced federal funding.

In 1993, the State of Iowa, through waivers, implemented reforms creating the Family Investment Program (FIP), a program similar to TANF created under PRWORA. The FIP's goals of helping program recipients leave poverty and become self-supporting parallel the intent of TANF and PRWORA (Holcomb et al., 1998; Iowa Department of Human Services 1996). The FIP merged and coordinated several existing programs and tied support for job training, education, child care, and transportation more directly to income transfers. Iowa has had to change FIP very little to meet current federal guidelines. Thus, Iowa has over six years of experience under a program with rules and incentives similar to those instituted only recently nationwide.

This paper examines the dynamics of welfare participation during the pre-TANF period of Iowa's welfare reform. The analyses make use of a unique data set containing linked state administrative records. These data are ideal studies across time because key variables are available on a monthly basis. This research has the specific objective of determining how programmatic, demographic and macroeconomic factors relate to dependence and recidivism among program participants. Along with providing insights into how TANF requirements might impact program participation among low-income families, this study also contributes to the literature through its use of administrative data for the empirical analyses and its rigorous attention to data-related estimation issues.

In section two, we review existing research. In section three, we outline the main features of the Iowa administrative data used here. We also discuss the benefits and drawbacks of using administrative data for research purposes. Section four details a key issue: the multiple imputation procedure used for assigning values to cases that do not report educational attainment. Section five provides descriptive analyses of the dynamics of FIP participation. In section six, we present a fixed effects model of welfare dependence and estimate the determinants of time staying on FIP. The fixed effect model allows us to control for unobserved heterogeneity. We employ a semiparametric duration model, and examine the distribution of the first period following exit from the program and incidence of recidivism. The semiparametric approach has the advantage of not requiring distributional assumptions on the duration of the exit spells. In section seven, we conclude the paper by drawing several policy implications from our findings.

Literature Review

The majority of the early literature on welfare participation focuses on either the probability of participation at a point in time (Moffitt 1983, 1986; Robins 1986; Blank 1989a; Blank and Ruggles 1996; Hu 1999) or exit rates related to a welfare spell (Plotnick 1983; O'Neil et al. 1987; Ellwood 1986; Blank 1989b; Fitzgerald 1991). These studies find that greater nonwage income, higher wage rates, more years of schooling, fewer children, good health, and being white are related to lower participation rates and higher exit rates. Moreover, these studies also show the existence of "negative duration dependence" that occurs when the exit rate falls as the duration of the welfare spell lengthens. Moffitt (1992) reviews the concepts and measures of welfare dependence presented in this early literature. He finds that the most common definition of welfare dependence focuses on the length of a single welfare spell; this measure does not consider the high reentry (recidivism) rates among welfare recipients.

National studies, most conducted using data collected prior to PRWORA and TANF, show that a substantial proportion of those who exited the Aid to Families with Dependent Children (AFDC) program, the predecessor of TANF, returned. Meyer and Cancian (1996) examine data from the 1979 National Longitudinal Survey of Youth (NLSY79) and find that 37 percent of women who exited returned within one year; 50 percent returned within two years. Harris (1996) examines the Panel Study of Income Dynamics data and finds that 27 percent of the welfare exiters returned in one year; 42 percent returned within two years. (www.isr.umich.edu/src/psid/)

Only recently, with increasing concern by policymakers about welfare dependence and recidivism, have researchers begun to look at welfare recidivism and multiple participation spells. Blank and Ruggles (1994) use the Survey of Income and Program Participation (SIPP) data to study short-term recidivism among households headed by single mothers with children under age 19. They find that 20 percent of former AFDC recipients returned to the program before the end of the sample period. Their results also show that the average post-AFDC spell is six months, implying that most of the single mothers returned to AFDC relatively quickly. Cao (1996), using NLSY79 data, confirms Blank and Ruggles's finding of considerable reoccurrence of welfare recipiency. Important determinants of recidivism identified in the literature include having fewer years of education, not being married, and having little job experience (Sandefur and Cook 1997; Brandon 1995). Cao's (1996) analyses indicate that initial welfare dependency and recidivism are correlated with the recipient's age, years of education, marital status, ethnic origin, and region.

Born et al. (1998) provide preliminary analyses of administrative data from the Maryland Family Investment Program. Nearly 20 percent of the cases they examined were reopened within the first three to six months post-exit. Reentry rates were lowest among women who exited for employment reasons. Born et al. also find that women whose exits were short-lived tended to have younger children than those women who managed to stay off of the program.

Each of these studies, with the exception of Born et al. (1998), is limited in two ways. First, they examine participation in and outcomes related to the recently abolished AFDC program. Second, each study relies on data obtained directly from program participants through surveys. The Joint Center for Poverty Research at Northwestern University's Advisory Panel on Research Uses of Administrative Data reports that "current national survey research data cannot adequately monitor the diverse, local programs currently being established by state and local governments." (Hotz et al. 1998). Hotz et al. continue by noting that the advantages of administrative data over survey data include the level of detail and accuracy of the data, larger sample sizes, and lower costs. Disadvantages of using administrative data for research include working with samples limited to individuals having experienced some event or some particular transaction; measures and variables collected to manage and monitor ongoing programs, not collected for research purposes; and time frames that correspond, in principle, to periods of being enrolled in a program. The current study advances the literature by examining effects and outcomes of an assistance program quite similar to the TANF programs that have been established in many states. Also, through analyses of administrative data, the current study is not hindered by biases inherent in analyses of data obtained through surveys.

Data

Iowa was one of the early states to link administrative data across programs to support program administration and policy analysis. In 1995, a project was designed to develop administrative data systems for research purposes. The product of this effort was a three-year (April 1993 to March 1996) longitudinal data file that matches and merges FIP, Medicaid, Food Stamp Program (FSP), child support, and quarterly earnings records for all FIP recipients during this period. The FIP, FSP, and Medicaid represent the key assistance programs for low-income families; child support and earnings are the key sources of nonpublic assistance income. These data are specific as to amounts (e.g., program benefits, child support received, and earnings) and dates (e.g., program exit and reentry). They are preferred over survey data because of their specificity. And, the data are not subject to problems related to respondent recall and respondent bias. Data are linked for all FIP recipients in April 1993. Observations (cases) are added to the file as they enter FIP; cases are followed throughout the data period, even after exiting FIP.

We supplement the administrative data file in two ways. First, we classify each county as being metro or nonmetro (Butler and Beale 1994). Second, we merge monthly county unemployment rates and county income per capita to account for the effect of local economic conditions in our analyses. Monthly county unemployment rates are available from the Iowa Workforce Development.

We create a two-year panel data set, beginning October 1993, the start of the FIP program, and ending September 1995. All cases identified as receiving FIP benefits in October 1993 (n=38,632) are included in the panel. No samples are drawn for these analyses. We observe 22,080 FIP exits among these cases, where exit is defined as being inactive (i.e., no benefits) for two months in a row. The total number of observations for the empirical analyses is reduced to 32,309 after deleting cases with missing information other than educational attainment.

Although the Iowa linked data set includes detailed information on child support collections, FIP participation, and quarterly wage earnings, the household and demographic variables are limited. Available information includes the educational attainment of the case head’s household, as well as age, marital status, ethnic origin, gender, disability status, and county of residence. The number of children in the household also is known. Unfortunately, it is not mandatory to provide educational attainment when applying for FIP, and about 50 percent of our observations have missing data on education. Comparison of the sample means of variables including and excluding observations with missing education fails to support the assumption that the occurrences of missing data on educational attainment are distributed randomly throughout the population. Because deleting nonrandom missing data would lead to biased estimates and a loss of information, we develop a statistical procedure for imputing education. The imputation procedure is discussed in detail in the next section.

Multiple Imputation Procedure for Missing Educational Data

We employ a multiple imputation procedure proposed by Herzog and Rubin (1983), and Rubin (1987), to compensate for missing educational attainment data. Multiple imputations are repeated random draws from a model generating nonresponse. This approach is favored over a single imputation because it incorporates the uncertainty about the accuracy of imputed values. Multiple imputation increases the efficiency of estimation and allows us to derive valid inferences simply by combining complete data inferences. This procedure also allows us to examine the sensitivity of inferences to different models that generate nonresponses.

The multiple imputation procedure begins by assigning each observation to one of six distributional patterns based on the availability of the educational attainment measure across the eight quarters of data. (See Table 1.). It is clear that most of the observations have either no missing data or data are missing completely for all eight quarters. These two groups account for almost 94 percent of the sample. Next we examine the distribution of the education variable for those cases with full information (n=16,010) to determine the algorithm of imputation. Table 2 details the distribution for this group relative to whether or not the case head had a high school degree at that time. As we expected, most individuals (97 percent) did not change categories over the two-year period. In other words, if an individual did not have a high school degree in October 1993, he/she did not receive it by September 1995. Twice as many case heads had a high school degree (63.8 percent) as did not (33.1 percent) in this group for which we have full information.

Next, we estimate a logit regression to predict educational attainment. We assume that educational attainment is related to (i.e., can be predicted by) a set of variables (N variables) that includes gender, race, marital status, an indicator of living in a metro county, the number of children in the household, quarterly wage income, total numbers of months on FIP, the amount of child support received, the county unemployment rate, and county income per capita. To account for the uncertainty about the accuracy of the imputed values, the estimated coefficients and their variance-covariance matrix are viewed as the posterior distribution of the true parameters. Hence, we have an N-variable normal distribution with means equal to the estimated coefficients and variance-covariance equal to the estimated variance-covariance matrix.

We draw a random sample of values for the N variables from the posterior normal distribution and use these drawn N coefficients to calculate the predicted probability of a specific educational status, for example, having a high school degree. Then, we randomly draw a value from a uniform distribution and compare it with the predicted probability. If the predicted probability (of having a high school degree) is greater than the random value, we assign the predicted education status (i.e., high school degree) to the missing value; otherwise, the alternative (no high school degree) is assigned. We repeat the above procedures five times using five sets of explanatory variable values randomly drawn from the posterior distribution. This approach results in five complete data sets that we use in our analyses of welfare dependence and recidivism.

The N x 1 column vectors of estimated parameters and variances can be obtained, respectively: $\underline{\hat{\beta}}_i$ and $\mathrm{Var}(\underline{\hat{\beta}}_i)$, i=1, 2, 3, 4, 5. Because we are interested in estimating the true parameter vector, $\underline{\beta}$, these 5 sets of $\underline{\hat{\beta}}_i$'s are combined to form the following inference about $\underline{\beta}$:

$\underline{\beta} - \underline{\hat{\beta}}^*$ *is approximately normally distributed with mean 0 and variance* $\mathrm{V}^* + \mathrm{B}$*,*

where $\underline{\hat{\beta}}^* = \sum_{i=1}^{5} \underline{\hat{\beta}}_i \Big/ 5$ and $V^* = \sum_{i=1}^{5} \mathrm{Var}(\underline{\hat{\beta}}_i) \Big/ 5$. B is an N x 1 column vector with elements $\mathrm{b}_{j1} = \sum_{i=1}^{5} (\hat{\beta}_{ij1} - \hat{\beta}_{\bullet j1}{}^*)^2 \Big/ 4,\ \mathrm{j} = 1, 2, 3, ..., \mathrm{N}$, where $\hat{\beta}_{ij1}$ and $\hat{\beta}_{\bullet j1}{}^*$ are the elements of $\underline{\hat{\beta}}_i$ and $\underline{\hat{\beta}}_i{}^*$, respectively. As a result, the variance estimates are the sum of (1) the average variances of the estimated variances and (2) the variances across the five multiple imputations.

The main challenge we face when imputing missing educational attainment is the computational difficulty of predicting the joint probabilities for eight quarters under an eight-variable normal distribution. That is, we must consider the eight separate quarters simultaneously. We make two simplifying assumptions to reduce the computational and modeling burden. First, we impute for only those cases with the patterns of missing data that are shown in Table 1. We delete the other 474 observations (1.6 percent) with missing educational data. Consequently, there are 16,299 observations with education missing for at least one quarter.

Second, given that 97 percent of the observations with full information did not change educational status over the two years (from Table 2), we use a “carryover” approach with the quarterly imputations. We first predict the joint outcome of quarter 1 and quarter 5 for observations with education missing in all quarters (n=14,674; row 2 from Table 1). Then, the predicted value of quarter 1 is carried over to quarters 2, 3, and 4, and the predicted value of quarter 5 is carried over to quarters 6, 7, and 8. For other cases with missing data in year 1 (n=320 and n=110; rows 4 and 5 from Table 1, respectively), we impute educational attainment for quarter 1 and carry over that value when data are missing in quarters 2, 3, and 4. Finally, we predict educational attainment in quarter 6 for observations in row 3 (n=1,195) of Table 1. The predicted value is carried over to quarters 7 and 8.

The multiple imputations generate 6,593 observations (40.5 percent) with no high school degree for two years, 9,436 observations (57.9 percent) with at least a high school degree for two years, and 270 observations (1.6 percent) experiencing a change in educational attainment (receiving their high school degree) some time during the two-year period.

Participation in the Family Investment Program (FIP)

We next examine the dynamics of FIP participation. During the data period, the overall FIP caseload initially increased and then fell. The initial caseload increases resulted from the more generous FIP income disregards and the stronger support programs that were introduced in 1993 (Fraker et al. 1998). Caseload characteristics are reported in Table 3 for the cases in the linked data set that we identify as being FIP active for October 1993, October 1994, and October 1995. We identify the active FIP caseload within about 3 percent for the three monthly periods reported in Table 3.[1] About 90 percent of the FIP cases received food stamps, and, as expected, almost all cases included households with children. Of these cases, 40 percent had a single adult with child(ren) and 87 percent of the case heads were female.

We are interested in knowing how many long-term welfare recipients in the first year, defined as receiving FIP benefits for at least seven months between October 1993 and September 1994, achieved economic self-sufficiency during the following 12-month period, October 1994 to September 1995.[2] We separate months on FIP in the first year into three distinct groups: 1-6 months, 7-11 months, and 12 months. The same classifications are applied to the second year (October 1994 to September 1995) except we add one more category: 0 months.[3]

Table 4 shows that in the first year, 83 percent (21.0 percent + 62.4 percent) of the FIP recipients are long-term recipients (7 months or more receiving FIP). This number drops to 58 percent (17.7 percent + 39.9 percent) in the second year. Recipients staying off of FIP for at least six months in the first year were more likely to continue this participation pattern or to become self-sufficient (annual numbers of months are 0) in the second year. Seventy-eight percent of short-term recipients (1-6 months) in the first year were nonrecipients in the second year. On the other hand, only about half of the long-term recipients (7-11 months and 12 months) in the first year have fewer months of receipt in the second year. Fifty-eight percent of those who were FIP recipients for all 12 months of the first year continued to stay on FIP for all of the second year.

Table 5 examines differences in case characteristics based on the length of FIP participation over the two-year period. We classify the sample into five mutually exclusive groups: (1) staying 0 months on FIP in the second year, (2) staying fewer months in the second year, (3) staying equal months in the second year, (4) staying more months in the second year, and (5) staying on all 24 months of the two-year period.

Table 5a reports annual averages for each year of data and the bottom panel provides growth rates between the two years. Note that relative to Table 4, we have deleted cases with missing values. As a result, the number of observations is reduced to 32,309.

It is clear that the majority of recipients had fewer months of FIP in the second year: 56 percent either did not receive FIP benefits or stayed fewer months on FIP in the second year; whereas only 6 percent of the cases were more dependent on FIP. Thirty-six percent of the cases, however, relied on FIP for all 24 months. The comparison of demographic characteristics for the five groups reveals that FIP recipients staying fewer months on FIP in the second year not only had higher average wage income, greater child support income, fewer children, and more years of schooling (Table 5a), but also experienced greater magnitudes of growth in wage income, child support, and the percentage of being married, as well as smaller increases in the number of children (Table 5b) compared with those with more months or all months on FIP. The most distinct contrast is between the “0 Month” and “Fewer Months” groups, and the “More Months” group. FIP recipients staying longer in the second year had almost no growth in wage income and a significant decline in the amount of child support received.

Results for the “percentage employed” and “quarters worked” show that although cases in the “24 Months” group have the lowest percentage of cases employed and the lowest average number of quarters worked, the growth rates for both variables are among the highest for the five groups. Their average wage income grew 28 percent. Unfortunately, as can be seen by the annual wage income for this group, they have the furthest to go to achieve economic self-sufficiency.

Sixty percent of cases in the “24 Months” group hold at least a high school degree. But, their average wage income is 40 percent lower than that of recipients staying fewer months in the second year. The percentage living in a metro county is stable over time and does not vary much across groups. An interesting finding is that both the “0 Month” and the “24 Months” groups have the lowest mobility rates (i.e., percentage of cases reporting moving to another county between year one and year two). By contrast, the “More Months” group has the highest mobility rate, nearly 12 percent.

Empirical Analysis of Welfare Dependence and Recidivism

We next examine welfare dependence through the annual number of months on FIP and recidivism through the duration of the first exit spell. We discuss the methods of analysis in detail in the following two subsections.

Welfare Dependence: Annual Number of Months on FIP

Method of Estimation and Definition of Variables. We estimate a fixed effect model to fully utilize our panel data. A fixed effect model allows us to control for unobserved heterogeneity, which will bias the estimates if ignored. The annual total months on FIP for each case in each year is our measure of "welfare dependence." A welfare recipient is said to have greater welfare dependence if he/she stays on FIP longer in a given year. Variables determining welfare dependence include total annual child support collections, predicted quarterly wage rate, average annual local unemployment rate, number of children in the household, an indicator of county of residence (metro or nonmetro), and marital status. Time invariant variables such as gender, race, and ethnic origin are excluded from the fixed effect model.

Because wage income is an important predictor of FIP participation, and because decisions regarding labor force and FIP participation are jointly determined, we use an instrumental variable approach to control for endogeneity. The instruments include age, education, local unemployment rate, gender, income per capita of the county of residence, share of county population with a college degree, and an indicator of residing in a metro county. We predict the highest quarterly income during the year instead of predicting annual wage income, because this measure better captures the labor market potential of FIP recipients.

We create four indicators for transitions in marital status during the year: (1) become married; (2) become divorced or separated; (3) remain single, and (4) remain married. Two additional variables, number of quarters being married and number of quarters being divorced or separated, are also calculated. They are used to form the following two interaction terms: (1) the number of quarters being married and the indicator for "become married" and (2) the number of quarters being divorced or separated and the indicator for "become divorced or separated". These two interaction terms allow us to estimate simultaneously the effects of changes in marital status and the length of time in the new status on annual total time on FIP. Table 6 presents the empirical definitions of variables and descriptive statistics for the sample used in the study.

Our empirical specification of the fixed effect model is as follows:

$$\begin{aligned} \text{MONTHS}_{ij} = \alpha_i &+ \beta_1 \text{CS}_{ij} + \beta_2 \text{PWAGE}_{ij} + \beta_3 \text{URATE}_{ij} + \beta_4 \text{NUMCHILD}_{ij} \\ &+ \beta_5 \text{DMARRIED}_{ij} + \beta_6 (\text{DMARRIED}_{ij} * \text{QMARRIED}_{ij}) \\ &+ \beta_7 \text{DDIVORCED}_{ij} + \beta_8 (\text{DDIVORCED}_{ij} * \text{QDIVORCED}_{ij}) \\ &+ \beta_9 \text{DSINGLE}_{ij} + \beta_{10} \text{DMETRO}_{ij} + \varepsilon_{ij} \\ i = 1, 2, 3, ..., n;\ & j = 1, 2, \end{aligned} \tag{1}$$

where α_i represents the effects of unobserved variables peculiar to the i^{th} individual and these effects remain constant over time, j represents the year, and ε_{ij} is the error term, which varies by individuals and time.

We expect that greater child support collections decrease the annual total time on FIP. On the other hand, a higher annual local unemployment rate and more children in the household should increase the annual total time on FIP. Predicted quarterly wage income is expected to be negatively related to total time on FIP. Living in metro counties could be positively related to annual total time on FIP because the stigma of welfare may not be as strong as it is for those living in nonmetro areas, or (and) the network of private support resources is not as great as it is for those living in nonmetro counties. Individuals who remain married for the entire year should have the fewest months staying on FIP relative to those with other marital status. As for the interaction terms, the longer a person is married (divorced or separated), the shorter (longer) he/she stays on FIP.

Empirical Results. The empirical results are reported in Table 7. Our model fits the data relatively well. The null hypothesis of a common intercept for all observations is rejected, suggesting that the fixed effect model is favored over ordinary least squares. The signs of the coefficients are consistent with the predictions and most are statistically significant at the 1 percent level. Using the estimated coefficients in Table 7, we calculate elasticities evaluated at the sample means.

We find that higher wage income significantly reduces the total time spent on FIP. Because we predicted quarterly wage income, the coefficient implies that if total annual wage income increases by $4,000 ($1,000 for each of four quarters), total time on FIP is reduced by 4.5 months. Expressed in elasticities, if total annual wage income increases by 1 percent, the annual number of months on FIP will decline by 1.12 percent. Greater child support collections reduce the annual total time on FIP. A $1,000 increase in annual child support reduces the average annual total months on FIP by 1.5 months. In terms of elasticity, the results show that annual total time on FIP falls by 0.1 percent when child support increases by 1 percent. If child support were to double (100 percent increase), the average annual total months on FIP would decrease by 10 percent or 0.86 months.

Local economic conditions have a strong effect on the annual total months on FIP. An increase of 1 percent in the unemployment rate would lengthen the annual stay on FIP by 1.3 months. The elasticity with respect to the local unemployment rate is 0.57, suggesting that the low unemployment rate in Iowa contributed to the decline in Iowa's FIP caseloads, and FIP caseloads are sensitive to changes in economic conditions. If the unemployment rate in the second year (3.59 percent) increases to a higher level, 5.5 percent for example, we could expect the annual total months on FIP to increase from 7 to 9.6 months. Consistent with other studies, the number of children in the household increases the annual number of months on FIP. One additional child in the household will add 0.38 months to the annual total months on FIP.

For marital status, the baseline group is those who remain married during the 12 months. The results indicate that the baseline group stays fewer months on FIP compared with others. FIP recipients who were married for 3 quarters during the year stay 0.17 (i.e., 1.43-0.42*3) months longer than the baseline group. Those married one and two quarters stayed 0.59 and 1.01 months longer, respectively. The "remain single" group stays 0.86 months longer on FIP than the baseline group. The coefficients on the indicator of divorced or separated and its interaction term have the expected signs, but are statistically insignificant. FIP recipients living in a metro county stay 0.5 months longer on FIP than do others, all else equal.

Welfare Recidivism: Duration of the First Exit Spell

Definitions of Variables and Distribution of First Exit Spells. We analyze the first exit spell to gain a better understanding of welfare recidivism. An exit is said to occur when a FIP recipient leaves the program for at least 2 consecutive months. Hence, an exit spell ranges between 2 and 23 months in our data. We require 2 consecutive months with $0 in FIP benefits to avoid problems with individuals counted as an "exit" due to administrative delays, or due to an individual not receiving a benefit in the short term to reasons of sanction or being eligible for a benefit of less than $10.[4] If the first exit spell of a case lasts only for a single month, we choose the next valid exit spell. There are 18,382 exit spells in our sample of 32,309 cases.

Column one in Table 8 shows the distribution for all exit spells. We further separate the exit spells into complete spells and right-censored spells because their distributions are different. Twenty-five percent of the exit spells are complete before the end of our sample period; the remaining spells are right-censored. The average length of all exit spells is 11 months. The average length of the complete spell, however, is six months, which suggests that for those who returned to FIP, the duration of their exit spell is relatively short. Also, our spell data reveal "negative duration dependence." That is, the probability of recidivism is a function of the length of the exit spell. The longer an individual stays off of FIP, the less likely she/he is to return to FIP.

Estimation Procedure. A semiparametric proportional hazard model with time-varying covariates is applied to our grouped duration data (Prentice and Gloeckler 1978; Kiefer, 1990). The advantage of the semiparametric method is that the baseline hazard is nonparametric and is estimated along with the coefficients of the explanatory variables through a maximum likelihood procedure.

We grouped the exit spells by duration into eight mutually exclusive time intervals. That is, reentry occurs in one of the following intervals [0, 4), [4, 7),…, [22, ∞), where a month is the unit of the measurement. The basic model assumes that, given a set of regressors, X_t, the density function of duration T, is $f(t, X_t)$, and its associated hazard function is

$$\lambda(t, X_t) = f(t, X_t) \Big/ \int_t^{\infty} f(s, X_t)\,ds\,. \qquad (2)$$

Because the exit intervals are $[0, a_1)$, $[a_1, a_2)$,…, $[a_i, \infty)$, the probability that T is greater than or equal to a_i, given that T is greater than or equal to a_{i-1}, can be expressed as

$$\text{Prob}\left[T >= a_i \middle| T >= a_{i-1}\right] = \exp\left[-\int_{a_{i-1}}^{a_i} \lambda(s, X_t)ds\right] = P_{a_i} \ , \tag{3}$$

where i=1, 2, 3,…, m and there are m+1 intervals. In other words, the probability of an exit spell ending in interval i is equivalent to the probability that a spell survives to interval i-1 and fails in interval i. Hence, the probability is given by

$$\text{Prob}(a_{i-1} <= T < a_i) = (1 - P_{a_i})\prod_{j=1}^{i-1} P_j \ . \tag{4}$$

We treat survival or failure (reentry) in each time interval as an observation. As a result, each FIP case contributes i observations to the likelihood function where i is the interval in which reentry takes place. Right-censored exit spells occur when the data period ends before the exit spell is completed. For the exit spell censored in a given interval, we assume that censoring occurs at the beginning of that interval. That is, if an exit spell is censored in interval i, we delete the i^{th} observation and only use i-1 observations. Given a sample with n individuals, the likelihood function is given as

$$L(\theta) = \prod_{k=1}^{n} (1 - P_{a_{ik}})^d \prod_{j=1}^{i-1} P_{a_j k} , \tag{5}$$

where d=0 if the individual is still at risk and d=1 if reentry occurs.

To estimate the likelihood function, we use a proportional hazard function $\lambda(t,X_t) = \lambda_0(t)\phi(\beta,X_t)$, where $\lambda_0(t)$ is the baseline hazard function and $\phi(\beta,X_t) = \exp(\beta' X_t)$. Instead of specifying the functional form for the baseline hazard, the semiparametric method estimates the baseline hazard function for each time interval. The resulting log likelihood function can be rewritten as follows:

$$\log L^*(\theta) = \sum_{k=1}^{n} \{1 - \exp[-\exp(r_{ik} + \beta' X_{tk})]\} - \sum_{k=1}^{n}\sum_{j=1}^{i-1} \exp(r_{jk} + \beta' X_{jk}) \ , \tag{6}$$

where $\theta = (r_1, r_2, ..., r_m, \beta)$

$$r_{ik} = \log[-\log\delta_i]$$

$$\delta_i = \exp\left[-\int_{i-1}^{i} \lambda_0(s)ds\right] .$$

δ_i is the conditional survival probability in interval i when $\beta' X_i$ is equal to zero.

Our model allows the values of the time-varying covariates to vary across different time intervals but requires them to remain constant within the time interval. The time-varying covariates include quarterly child support collections, educational attainment, marital status, number of children, an indicator of the area of residence (metro county vs. nonmetro county), and the quarterly local unemployment rate. Time invariant variables are gender and race (white or nonwhite).

Empirical Results. The average estimates of the duration model are reported in Table 9. We identify several important factors affecting FIP reentry. Higher quarterly wage income reduces the reentry hazard. Child support is also negatively related to the probability of reentering FIP in a given interval. Surprisingly, the hypothesis that a higher current unemployment rate increases the probability of reentry is not supported here. The estimated coefficient is insignificant.[5] Race and marital status do not affect the reentry rate either. Males are less likely to return to FIP than females. Families with a greater number of children are more likely to return to welfare. Living in a metro county decreases the reentry hazard, but the coefficient is not statistically significant.

The estimated coefficients R1 to R7 in Table 9 are used to calculate the hazard rate. Figure 1 shows the shape of the reentry (hazard) rate, which is estimated at the sample means of the explanatory variables. The hazard rate decreases almost monotonically as the exit spell lengthens, confirming the existence of negative duration dependence. In the first quarter, the hazard rate is 0.11. By the end of the seventh quarter, the hazard rate decreases to nearly 0.05.

Conclusions

We examined the dynamics of welfare participation and the initial experience of welfare reforms in Iowa. Half of the FIP recipients we followed in this study left the program within two years. Although improvements in the Iowa economy account for a share of the exits, our results provide some evidence that Iowa's reform of its welfare program as well may have helped reduce the FIP caseloads.

Analysis of the dynamics of FIP participation reveals that, on average, FIP recipients stayed fewer months on FIP in the second year of the study. However, 58 percent of those on FIP throughout the first year remained on FIP during the second year. The decline in the average annual total months on FIP is attributed mainly to cases staying on FIP for less than six months in the first year. At the same time, there exists a group of FIP recipients who experience great difficulties in achieving self-sufficiency. Thirty-six percent of FIP cases in our data stayed on FIP for the full two years (Table 5). Under TANF, the five-year lifetime limit on receiving benefits may affect this group in a few years. They may be without assistance if state governments can exempt only 20 percent of their caseloads from the time limit.

We find that FIP recipients who spent fewer months on FIP in the second year not only had more years of schooling, fewer children, higher earnings and child support, but also experienced greater growth in earnings and child support compared with those who had more months on FIP (Table 5). Multivariate analyses confirm that these factors are key determinants for both annual total months on FIP and welfare recidivism. Local economic conditions also have an effect on the annual total months on FIP. This finding suggests that we can expect an increase in TANF caseloads if the economy slows.

The average length of a completed exit spell is six months, implying that FIP recipients who returned to the program did so quickly. In simulations not reported here, we find that the marginal effects of increasing child support and wage income diminish as the duration of the exit spell lengthens. In other words, given that the exit spell is short, child support and wage income are crucial in determining the chances of exiting from FIP and of continuing to stay off of FIP during the early months of the exit.

The lessons learned here provide a preliminary indication of what we can expect from a state TANF program. Iowa's experience suggests that human capital, child support, marital status, and the presence of children are major determinants of welfare dependence and recidivism. Social policies aimed at helping families achieve economic self-sufficiency should help assistance program participants finish their formal education, provide and impose job training and job search, and further enforce the support of children by noncustodial parents. The effects of marital status on reducing welfare dependency and recidivism suggest that the parental responsibility initiatives currently underway in Iowa also have potential to help low-income families achieve economic self-sufficiency. Clearly, more years of data are needed to estimate fully the effect of welfare reform on Iowa's FIP population. Particularly, it is important to continue to follow those who left the program and to compare their socioeconomic conditions before and after the exit.

Finally, the empirical analyses for this study were conducted using state administrative data. Having the opportunity to use administrative data for research is a mixed blessing. These data made it possible to conduct analyses that could not have been conducted with survey data. On the other hand, they have their own challenges and limitations relative to survey data that cannot be ignored. We addressed one of these challenges in detail: the problem of missing data for a key explanatory variable (educational attainment). Based on our experiences with these data for this and other studies, we find that research based on administrative data complements well traditional survey-based research and should be encouraged.

Table 1. Distribution of educational attainment variable by quarters: October 1993 to September 1995

Observations (Percent of Total)	**Patterns by Quarter**							
	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q6**	**Q7**	**Q8**
16,010 (48.8%)	√[a]	√	√	√	√	√	√	√
14,674 (44.7%)								
1,195 (3.6%)	√	√	√	√	√			
320 (1.0%)		√	√	√	√	√	√	√
110 (0.3%)					√	√	√	√
474 (1.6%)	All Other Patterns							
Total Observations = 32,783								

[a] √ represents data are not missing.

Table 2. Distribution of observations with full educational attainment information: October 1993 to September 1995

Observations (Percent of Total)	**Patterns**							
	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q6**	**Q7**	**Q8**
10,230 (63.80%)	1[c]	1	1	1	1	1	1	1
303 (1.90%)	0	1	1	1	1	1	1	1
32 (0.20%)	0	0	1	1	1	1	1	1
28 (0.17%)	0	0	0	1	1	1	1	1
59 (0.37%)	0	0	0	0	1	1	1	1
29 (0.18%)	0	0	0	0	0	1	1	1
17 (0.10%)	0	0	0	0	0	0	1	1
26 (0.16%)	0	0	0	0	0	0	0	1
5,286 (33.12%)	0	0	0	0	0	0	0	0
Total observations = 16,010								

[a] 0 = does not have a high school degree. 1 = has at least a high school degree.

Table 3. FIP caseloads by demographic variables : October 1993, October 1994, and October 1995

Demographic Variables	OCTOBER 1993 Number of Cases (Proportion of Identified Cases)	OCTOBER 1994 Number of Cases (Proportion of Identified Cases)	OCTOBER 1995 Number of Cases (Proportion of Identified Cases)
Actual FIP Regular + UP Caseload[a]	37,600	38,776	34,246
Total Caseload as Identified in Data	38,632	39,917	35,509
On Food Stamp Program	(0.89)	(0.89)	(0.88)
Number of Children			
No Child	(0.01)	(0.01)	(0.01)
One Child Case	(0.35)	(0.35)	(0.35)
Two Children Case	(0.32)	(0.31)	(0.31)
More Than Two Children Case	(0.32)	(0.33)	(0.33)
Area of Residence			
Living in Metro	(0.53)	(0.53)	(0.53)
Living in Urban Nonmetro	(0.17)	(0.17)	(0.17)
Living in Rural Adjacent	(0.15)	(0.15)	(0.15)
Living in Rural Nonadjacent	(0.15)	(0.15)	(0.15)
Earnings and Child Support			
Family Had Wage Earnings	(0.58)	(0.65)	(0.68)
Family Received Child Support	(0.22)	(0.23)	(0.22)
Number of Adults			
No Adult	(0.01)	(0.01)	(0.01)
One Adult Case	(0.41)	(0.39)	(0.39)
Two Adults Case	(0.34)	(0.35)	(0.35)
More Than Two Adults Case	(0.24)	(0.25)	(0.25)
Gender			
Male	(0.13)	(0.13)	(0.13)
Female	(0.87)	(0.87)	(0.87)
Ethnicity			
White	(0.78)	(0.78)	(0.78)
Black	(0.11)	(0.11)	(0.11)
Others	(0.03)	(0.03)	(0.03)
Missing	(0.08)	(0.08)	(0.08)
Age of Case Head			
Younger Than 18	(0.03)	(0.02)	(0.02)
Between Age 18 and 21	(0.06)	(0.05)	(0.05)
Older Than 21	(0.91)	(0.93)	(0.93)
Educational Attainment			
High School, GED or More	(0.28)	(0.30)	(0.26)
Less Than High School	(0.19)	(0.15)	(0.17)
Unknown and Missing	(0.53)	(0.55)	(0.57)
Age of Youngest Child			
No Children	(0.01)	(0.01)	(0.01)
Younger Than 1	(0.18)	(0.17)	(0.17)
Between 1 and 3	(0.26)	(0.25)	(0.25)
Between 3 and 6	(0.22)	(0.24)	(0.24)
Older Than 6	(0.33)	(0.33)	(0.33)

[a] Obtained from Iowa Department of Human Services monthly reports.

Table 4. Dynamics of FIP participation in Iowa: October 1993 to September 1995[a]

Total Time on FIP in the First Year	**Total Time on FIP in the Second Year**				
	0 Month	**1-6 Months**	**7-11 Months**	**12 Months**	**Total**
1-6 Months	78.4 (50.6)[b]	12.0 (11.9)	6.5 (6.1)	3.2 (1.3)	(16.6)
7-11 Months	50.5 (41.3)	19.4 (24.4)	15.9 (18.9)	14.2 (7.5)	(21.0)
12 Months	3.4 (8.2)	17.1 (63.7)	21.3 (75.0)	58.3 (91.2)	(62.4)
Total	25.7	16.7	17.7	39.9	100.0

[a] Number of observations = 38,632.
[b] The first number is the row percentage. The number in parentheses is the column percentage.

Table 5a. Comparison of selected demographic variables among five patterns of participation: October 1993 to September 1995

Variables	**0 Months in Year 2 N=8,177 (25.3%)**		**Fewer Months in Year 2 N=9,921 (30.7%)**		**Equal Months in Year 2 N=379 (1.2%)**		**More Months in Year 2 N=1,990 (6.2%)**		**All 24 Months i Year 2 N=11,842 (36.6%)**	
	Yr. 1	**Yr. 2**	**Yr. 1**	**Yr. 2**	**Yr. 1**	**Yr. 2**	**Yr. 1**	**Yr. 2**	**Yr. 1**	**Yr. 2**
Annual Wage Income	9,126	12,182	7,278	11,347	8,618	9,882	8,678	8,697	5,538	7,07
Annual Child Support	630	1,122	218	696	369	411	434	272	156	17
Number of Children	2.04	2.05	2.16	2.24	2.18	2.25	2.19	2.31	2.27	2.3
High School or Above[a]	0.64	0.66	0.62	0.64	0.58	0.60	0.57	0.59	0.59	0.6
Married	0.22	0.23	0.19	0.20	0.23	0.25	0.22	0.22	0.18	0.1
Percentage Employed	0.80	0.77	0.79	0.88	0.88	0.89	0.84	0.85	0.65	0.7
Quarters Worked	2.58	2.72	2.41	3.0	2.89	2.98	2.75	2.74	1.93	2.3
Living in Metro County	0.51	0.51	0.53	0.53	0.47	0.48	0.53	0.52	0.55	0.5
Move to Other County	0.06		0.09		0.11		0.12		0.06	

Table 5b. The growth rates of selected demographic variables between the first year and the second year among five dynamic participation patterns

Annual Wage Income	33.5	55.9	14.6	0.2	27.6
Annual Child Support	78.1	219.0	11.3	-37.3[b]	12.8
Number of Children	0.5	3.7	3.2	5.4	4.4
Married	4.5	5.3	8.7	0.0	0.0
Percentage Employed	-3.7	11.4	1.1	1.2	15.4
Quarters Worked	5.4	24.5	3.1	-0.3	19.6

N=32,309

[a] The average of 5 imputation data sets is reported.

[b] Decline in child support is the combination of an increase in cases that did not receive child support and a decrease in the amount paid for those receiving child support.

Table 6. Definitions, means, and standard errors of variables

Variable	Mean (Standard Error)	Definition
Spell	8.566 (4.53)	Annual number of months on FIP
Male	0.091 (0.29)	Dichotomous variable equals 1 if FIP recipient is male
White	0.840 (0.36)	Dichotomous variable equals 1 if FIP recipient is white
DSCHOOL	0.615 (0.49)[a]	Dichotomous variable equals 1 if FIP recipient has a high school degree
PWAGE	7.610 (0.34)[a]	Predicted quarterly wage income (thousand)
CS	0.449 (1.08)	Annual child support collections (thousand)
URATE	3.762 (0.95)	Annual average local unemployment rate (percent)
NUMCHILD	2.209 (1.31)	Number of children at the beginning of the year
DMARRIED	0.041 (0.20)	Dichotomous variable equals 1 if married during the year
QMARRIED	0.111 (0.55)	Number of quarters being married
DDIVORCED	0.011 (0.10)	Dichotomous variable equals 1 if divorced or separated during the year
QDIVORCED	0.03 (0.27)	Number of quarters being divorced or separated
DSINGLE	0.760 (0.43)	Dichotomous variable equals 1 if remained single through the year
DMETRO	0.531 (0.50)	Dichotomous variable equals 1 if lived in metro counties

[a] The average of five imputation data sets is reported.

Table 7. Average coefficients of the fixed effect model on annual total numbers of months on FIP: October 1993 to September 1995[a]

Independent Variables	**Coefficients**
PWAGE	-4.450 (0.066)[b]***
CS	-1.450 (0.056)***
URATE	1.303 (0.041)***
NUMCHILD	0.381 (0.05)***
DMARRIED	1.433 (0.34)***
DMARRIED x QMARRIED	-0.420 (0.13)***
DDIVORCED	-0.540 (0.55)
DDIVORCED x QDIVORCED	0.362 (0.23)
DSINGLE	0.860 (0.20)***
DMETRO	0.494 (0.14)***
Adjusted R-Squared	0.61
Number of Observations	32,309

Dependent variable: Annual Total Number of Months on FIP

[a] The coefficients and standard deviations for each of the 5 imputed data are reported in Table 10 in Appendix A

[b] Standard errors are in the parentheses.

*** significant at 1 percent level.

Table 8. Distribution of Exit Spells: October 1993 to September 1995

Duration of Spell	All Spells	Complete Spells	Right-censored Spells
2	1,596	963 (60)[a]	633 (40)
3	1,427	731 (51)	696 (49)
4	1,143	482 (42)	661 (58)
5	963	439 (46)	524 (54)
6	926	382 (41)	544 (59)
7	805	313 (39)	492 (61)
8	750	263 (35)	487 (65)
9	806	168 (21)	638 (79)
10	711	142 (20)	569 (80)
11	766	127 (17)	639 (83)
12	863	120 (14)	743 (86)
13	772	97 (13)	675 (87)
14	732	87 (12)	645 (88)
15	743	64 (9)	679 (91)
16	714	42 (6)	672 (94)
17	605	39 (6)	566 (94)
18	636	33 (5)	603 (95)
19	587	27 (5)	560 (95)
20	615	20 (3)	595 (97)
21	751	18 (2)	733 (98)
22	746	6 (1)	740 (99)
23	725		725 (100)
Mean Duration	11.10	6.00	12.78
Numbers of Exit Spells	18,382	4,563	13,819

[a] Row percentages are in parentheses.

Table 9. Average maximum likelihood estimates of recidivism: October 1993 to September 1995[a]

Independent Variables	Coefficients
Predicted Wage	-0.045 (0.02)[b]**
Child Support	-0.463 (0.04)***
Local Unemployment Rate	-0.039 (0.02)
White (0,1)	0.036 (0.04)
Married (0,1)	-0.002 (0.03)
Male (0,1)	-0.153 (0.05)***
Number of Children	0.110 (0.01)***
Living in Metro County (0,1)	-0.050 (0.03)
Other Parameters Estimated	
R7	-2.875 (0.241)***
R6	-3.166 (0.221)***
R5	-2.857 (0.21)***
R4	-2.761 (0.20)***
R3	-2.397 (0.20)***
R2	-2.077 (0.19)***
R1	-2.052 (0.19)***
Number of Observations	18,382
Log Likelihood[b]	(-15,735.6, -15736.1)[c]

[a] The coefficients and standard deviations for each of the 5 imputed data are reported in Table 11 in Appendix A

[b] Standard errors are in parentheses.

[c] The lower and upper bounds of the values of five log likelihood functions are reported.

*** significant at 1 percent level.

** significant at 5 percent level.

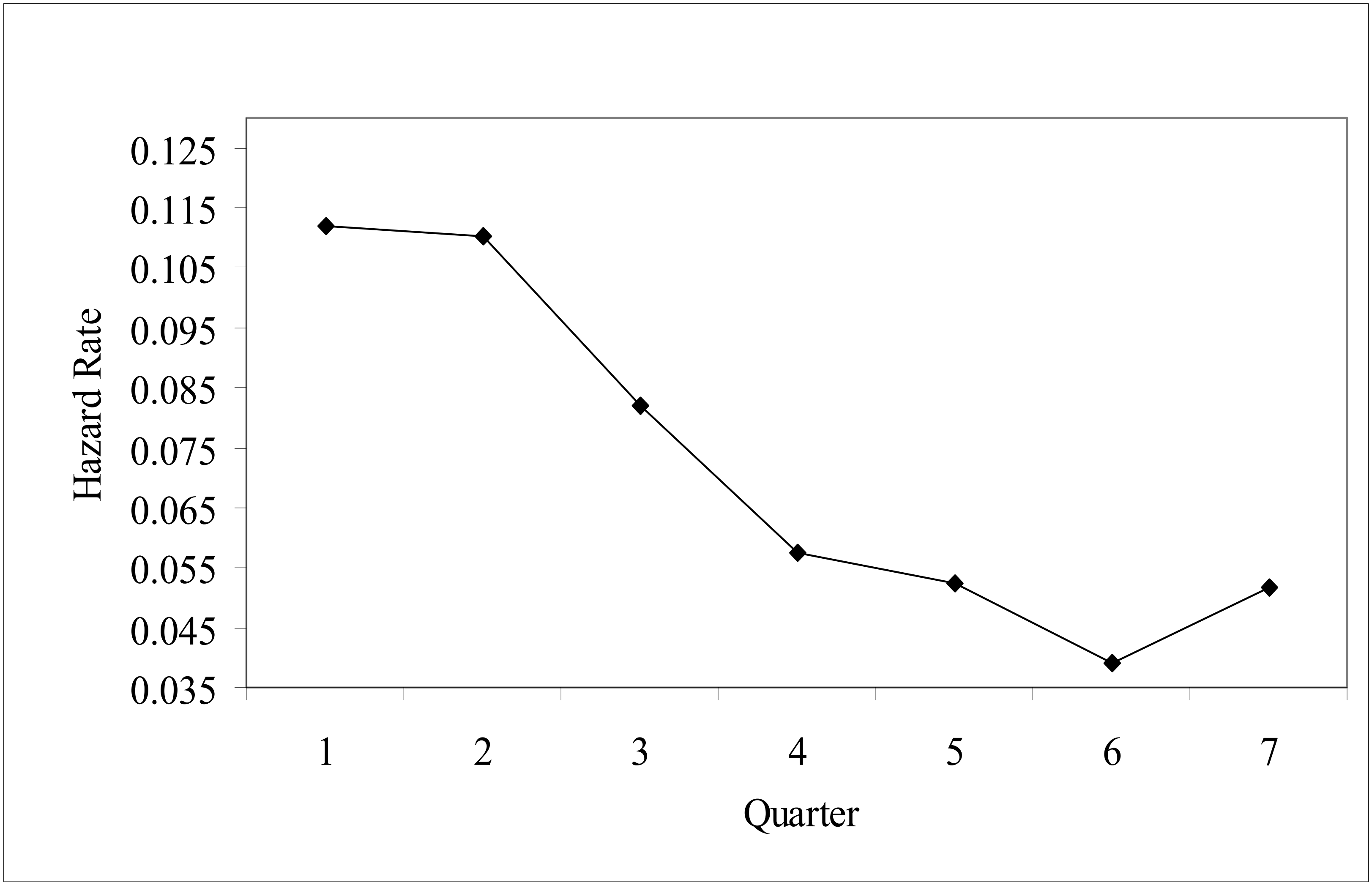

Figure 1. Predicted hazard rate evaluated at the sample means.

Endnotes

[1] It is not obvious within the data set whether or not a case is receiving FIP benefits currently. Our average monthly error in identifying the actual caseload over the 27-month period October 1993 through December 1995 was 2.1 percent. Although in each of the Octobers reported here we overestimate the caseload, this was not always the case.

[2]. Note that our data are left censored. That is we do not have information about the case and case members prior to April 1993. Further, for these analyses, we do not make use of information prior to the start of the FIP program, October 1993. Thus, long-term recipients are defined as having at least seven months of benefit receipt within this specific 12-month window. Recipients not classified as long-term in these analyses may have actually received AFDC benefits for seven months or more prior to October 1993.

[3.] Recall that our sample consists of FIP recipients in October 1993. Therefore, by definition, 0 months of receipt in the first year is not possible.

[4.] Program rules are such that a FIP program participant eligible for a cash benefit of less than $10 in a given month does not receive a cash benefit that month, but continues to remain eligible for, and must participate in, all other aspects of the program as if she/he had received a cash benefit.

[5] We also tried to lag the local unemployment rate but the coefficient remained insignificant.

Appendix A

Table A-10. Coefficients from the fixed effect model on annual total numbers of months on FIP: October 1993 to September 1995

Independent Variables	Endogenous Variable: Annual Total Numbers of Months on FIP				
	Sample 1	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**
PWAGE	-4.445 (0.09)[a]***	-4.453 (0.06)***	-4.447 (0.06)***	-4.450 (0.06)***	-4.462 (0.06)**
DWAGE	-1.447 (0.02)***	-1.446 (0.02)***	-1.447 (0.02)***	-1.446 (0.02)***	-1.446 (0.20)**
URATE	1.305 (0.04)***	1.301 (0.04)***	1.307 (0.04)***	1.30 (0.044)***	1.303 (0.04)**
NOCHILD	0.381 (0.05)***	0.381 (0.05)***	0.381 (0.05)***	0.380 (0.05)***	0.383 (0.05)**
DMARRIED	1.437 (0.34)***	1.430 (0.34)***	1.436 (0.34)***	1.421 (0.34)***	1.442 (0.34)**
DMARRIED x QMARRIED	-0.425 (0.13)***	-0.424 (0.13)***	-0.424 (0.13)***	-0.421 (0.13)***	-0.426 (0.13)**
DDIVORCED	-0.538 (0.55)	-0.546 (0.55)	-0.533 (0.55)	-0.543 (0.55)	-0.539 (0.55)
DDIVORCED x QDIVORCED	0.362 (0.23)	0.365 (0.23)	0.361 (0.23)	0.360 (0.23)	0.364 (0.23)
DSINGLE	0.863 (0.20)***	0.854 (0.20)***	0.869 (0.20)***	0.844 (0.20)***	0.869 (0.20)**
DMETRO	0.490 (0.14)***	0.496 (0.14)***	0.503 (0.14)***	0.480 (0.14)***	0.502 (0.137)*
Adjusted R-Squared	0.61	0.61	0.61	0.61	0.61
F Statistics	4565.5	4565.5	4565.5	4565.5	4565.5
Number of Observations	32,309	32,309	32,309	32,309	32,309

[a] Standard errors are in parentheses.
*** significant at 1 percent level.

Table A-11. Coefficients from the maximum likelihood estimates of recidivism: October 1993 to September 1995

Independent Variables	**Endogenous Variable: Annual Total Numbers of Months on FIP**				
	Sample 1	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**
Predicted Quarterly Wage Income	-0.045 (0.02)**	-0.045 (0.02)**	-0.047 (0.02)**	-0.04 (0.02)**	-0.048 (0.02)*
Total Child Support Collections	-0.463 (0.04)***	-0.463 (0.04)***	-0.462 (0.04)***	-0.463 (0.04)***	-0.462 (0.04)*
Local Unemployment Rate	-0.013 (0.02)	-0.013 (0.02)	-0.014 (0.02)	-0.013 (0.01)	-0.14 (0.02)
White	0.036(0.04)	0.036 (0.04)	0.036 (0.04)	0.036 (0.04)	0.036 (0.04)
Married	-0.002 (0.03)	-0.002 (0.03)	-0.002 (0.03)	-0.002 (0.03)	-0.002 (0.03)
Male	-0.153 (0.05)***	-0.154 (0.05)***	-0.153 (0.05)***	-0.154 (0.05)***	-0.153 (0.05)*
Number of Children	0.11 (0.01)***	0.11 (0.01)***	0.11 (0.01)***	0.11 (0.01)***	0.11 (0.01)**
Living in Metro County	-0.05 (0.03)	-0.05 (0.03)	-0.05 (0.03)	-0.05 (0.03)	-0.05 (0.03)
Other Parameter Estimated					
R7	-2.875 (0.24)***	-2.878 (0.24)***	-2.859 (0.24)***	-2.91 (0.24)***	-2.853 (0.24)*
R6	-3.166 (0.22)***	-3.17 (0.22)***	-3.151 (0.22)***	-3.20 (0.22)***	-3.145 (0.22)*
R5	-2.857 (0.21)***	-2.86 (0.21)***	-2.842 (0.21)***	-2.89 (0.21)***	-2.836 (0.21)*
R4	-2.761 (0.20)***	-2.764 (0.20)***	-2.746 (0.20)***	-2.795 (0.20)***	-2.74 (0.20)**
R3	-2.397 (0.20)***	-2.40 (0.20)***	-2.382 (0.20)***	-2.431 (0.20)***	-2.377 (0.20)*
R2	-2.077 (0.19)***	-2.08 (0.19)***	-2.063 (0.19)***	-2.109 (0.19)***	-2.057 (0.19)*
R1	-2.052 (0.19)***	-2.054 (0.19)***	-2.038 (0.19)***	-2.083 (0.19)***	-2.032 (0.19)*
Number of Observations	18,382	18,382	18,382	18,382	18,382
Log Likelihood	-15,735.8	-15,735.8	-15,735.7	-15,736.1	-15,735.6

[a] Standard errors are in parentheses.
*** significant at 1 percent level.
** significant at 5 percent level.

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